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Leveraging Inception V3 for Precise Early and Late Blight Disease Classification in Potato Crops

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ABSTRACT

The global significance of potato (Solanum tuberosum) as a staple food necessitates innovative approaches to safeguard its production against detrimental fungal pathogens, notably early and late blight diseases. These afflictions not only jeopardize crop health but also exacerbate economic pressures on agricultural stakeholders by diminishing yields and necessitating increased use of chemical treatments, which in turn degrades soil quality and elevates disease susceptibility. In response to these challenges, the deployment of Artificial Intelligence (AI) offers a transformative solution for the automatic detection of plant diseases, minimizing human intervention and maximizing diagnostic precision. This study employs the Inception V3 model, a deep learning algorithm, on a dataset comprising 2,152 potato leaf images, segmented into training and validation subsets at an 80:20 ratio. Through the application of image augmentation techniques such as scaling, rotating, and flipping, the diversity of the dataset was substantially enhanced, facilitating the model's capacity to distinguish between early blight, late blight, and healthy leaves with an unprecedented accuracy of 98.60%. This research not only underscores the efficacy of AI in revolutionizing agricultural disease management but also contributes to the broader discourse on sustainable farming practices by reducing reliance on chemical interventions. The findings advocate for the integration of AI-driven diagnostic systems in agricultural management, promising significant advancements in crop preservation and economic sustainability.

1. INTRODUCTION

One of the important causes restricting agricultural produce and adversely affecting the economy of the nation and the income of farmers is the presence of pests and crop diseases. Early and non-destructive identification of pests and crop diseases is the most vital factor in the development of precision agriculture [1-4].

Potatoes (Solanum tuberosum) are a variety of edible plant tubers that grow in the roots of the plant. It is one of the most important food crops and has a high consumption rate across the world. Potatoes are highly vulnerable to infections of fungal and bacterial types; thus, disease-free, healthy potato plants have to be planted with much care in the growing areas. The wide range of diseases causes difficulty in the prediction, diagnosis, and control measures of their spread and occurrence. Devastating consequences and severe losses have come up as a limitation in potato cultivation [5].

Apart from being majorly used in cuisine, potatoes also contribute to the economic growth of many nations, including New Zealand, the US, and the UK; thus, millions of hectares of land are dedicated around the globe to potato cultivation. Potatoes are also a rich source of antioxidants, fiber, carbohydrates, minerals like potassium, magnesium, etc., and various vitamins, including vitamins B6 and C. They are a staple and versatile food in many regions and are found to be naturally gluten-free. They may help in controlling blood sugar levels and also improve the digestive health of humans [6, 7]. These medicinal benefits of potatoes add extra importance to the cultivation of potatoes. Many plants have medicinal benefits in their shoot parts, like lettuce, barley, etc. [8, 9]. The growth of medicinal herbaceous plants can also be enhanced by cultivating them in smart precision agricultural setups using IoTs or green IoTs [10]. Great losses occur in potato cultivation due to several factors, which in turn disturb the economies of productive nations. The major causes of potato disease are pests and plant diseases. Early detection of the diseased leaves of potato plants may go a long way toward saving the crop. This is becoming a major challenge due to the wide variety of crop species that are affected in different ways when subjected to different environmental conditions, and it leads to a delay in the detection of leaf diseases. Several machine learning and deep learning algorithms have been developed to help in the early detection of potato leaf diseases [11]. A major issue found in the existing systems is the efficiency obtained by implementing the algorithms.

Table 1. Classification of fungal plant diseases

Image	Disease Name	Causes and Symptoms	Climatic Conditions
	Early Blight	It is caused by a fungus named Alternaria solani. Infected leaves develop dark brown patches of 3-4 mm in diameter.	Early blight is found in cool, moist climatic conditions. Temperatures ranging within 75°-84°F and prolonged wetness of leaves due to frequent rainfall or sprinkler irrigation, together cause early blight infections.
	Late Blight	It is caused by Phytophthora infestans, an oomycete pathogen. Late blight is characterized by a circular brown infection, surrounded by pale greenish-yellow tissue.	Late blight is found when temperatures are mild and humid for prolonged periods. Temperatures ranging within 60°-78°F and humidity above 90%, together cause early blight infections.

Table 1 describes the two types of potato leaf diseases: early blight and late blight. These are fungal diseases that cause increased damage to plants in climatic conditions that enhance the growth of fungal infection.

A wide range of fungal and bacterial diseases affect the potatoes on the foliage and later spread throughout the entire plant. This causes serious damage to the block as a whole. Many of the diseases destroy the tubers first and then affect the leaves, causing the plant to wilt. Irrespective of the initial occurrence of the disease, the control action against fungal and bacterial diseases in potato plants must not be delayed [12]. Smart precision agriculture is useful in promoting the development of environmentally sustainable farming methods, ensuring food safety, enhancing economic growth, and protecting human health.

The proposed potato leaf disease detection model was trained in 1937 and validated on 215 images from a dataset of 2152 images of potato leaves. This technique proves to achieve 98.60% accuracy on this dataset. Finally, the performance of the proposed technique is compared with the existing state-of-the-art models and found to be better in terms of accuracy. At first, the Exploratory Data Analysis (EDA) is done, which helps us analyze the entire dataset and summarize its main characteristics, like class distribution, size distribution, and so on. It consists of brief analyses of the dataset considered so that the modeling process gets a direction and addresses preliminary queries. It may comprise the distribution of variables and verifying relevant patterns for various classes. Visual methods are often used to display the results of this analysis. Image pre-processing is carried out in the next step, where the features of the raw data are improved by suppressing the unnecessary distortions and making the data more suitable for the model by resizing and enhancing the important features and improving the performance. This holds for image classification as well, from which meaningful information can be extracted.

The authors [5] have proposed an improved deep learning algorithm that classifies the potato leaf images into five classes with 97.2% accuracy. The authors [12] used CNN to classify five types of potato leaf diseases on a dataset of 5000 images and obtained improved accuracy over R-CNN, AlexNet, Transfer Learning, VGG, and GoogLeNet. There are numerous challenges involved in the process of crop disease detection, namely: the evolution of new pathogens, generalization of the used model, technological dependency, collection of high-quality data, etc. [6-13].

In this research work, the authors have used a convolutional neural network (CNN), namely, Inception V3. Inception V3 is a deep learning (DL)-based CNN model mainly used for image classification. It is the third version of Google's Inception CNN, which is advanced and optimized to assist in image analysis and object detection. Along with restraining the count of parameters from increasing beyond a limit, the design of Inception V3 aims at allowing deeper networks. Some of the advantages of using the Inception V3 model as compared to its contemporaries like GoogLeNet, BN-Inception, PReLU, and VGG Net can be listed as [13, 14]:

- It shows better efficiency than the Inception V1 and V2 models.
- It shows a lower error rate while maintaining the same speed as compared with the previous models.
- It is a more advanced version and has a deeper network as compared to the previous versions.
- It is comparatively less expensive.

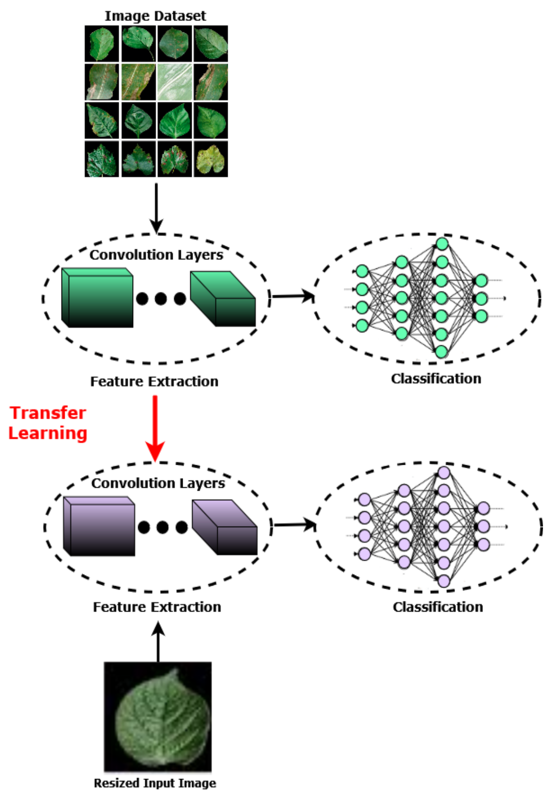


Figure 1. Depiction of the working of a pre-trained model when used to classify a new image dataset

The motivation for using transfer learning techniques for crop disease detection lies in the fact that a deep learning model takes a substantial amount of time to be trained and also requires a lot of samples to be trained with millions of parameters, whereas in transfer learning models, these problems are overcome. The flaws of deep learning models are overcome by transfer learning (pre-trained) models. In pre-trained models, the training time is reduced, which also ensures better accuracy. This research gap in classification problems is overcome using pre-trained transfer learning models. Inception V3, ResNet 50, VGG 19, and AlexNet are some of the widely used transfer learning models. With the help of transfer learning techniques, knowledge is transferred from a pre-trained model to another model that will perform classification. This reduces the training time, so the training time is saved. Figure 1 represents the workings of the transfer learning model to train a new model to classify a new image dataset.

The key contributions of this research are pointed out as follows:

(1) Collecting the image dataset of potato leaves and preprocessing it.

(2) Augmenting the dataset and splitting it into training and validation datasets.

(3) Training the Inception V3 CNN model to efficiently recognize and classify two types of diseased potato leaves and healthy leaves.

(4) Classifying the dataset with enhanced efficiency and reduced time.

(5) Comparison with the existing state of the art.

This approach significantly reduces the error rate and gives an accuracy of over 98%.

The rest of the article is organized as follows: an extensive background study in this regard has been done in Section 2, materials and methods are discussed in Section 3, results and discussion are described in Section 4, Section 5 depicts the comparison of the obtained results with the existing works, and Section 6 presents the conclusion and future work of the research work.

2. RELATED WORK

The conventional method of detecting diseases and pests in crop leaves includes the process of collecting actual samples of pictures from the fields and manually analyzing them using labor-intensive chemical methods. This time-consuming diagnostic process has a lot of other limitations, too. Many visible imaging methods use infrared (IR) imaging techniques to retrieve pictures of images [15, 16]. You can use machine learning and image processing techniques like erosion, segmentation, feature extraction, and more to look for changes in the chemical content, outer features, and physiological structure of crop leaves in order to diagnose diseases. The authors [17] have applied ML and traditional image processing techniques to check and identify the targets of various pests on crops based on the retrieved hyperspectral and IR images. The authors [18] have worked on CNN architecture to identify the diseases of potato leaves. A combination of IR image information and information on the depth to find a diagnosis of powdery mildew of tomato leaves using Support Vector Machines (SVM) was used by the authors [19]. ML methods are used to identify and analyze hyperspectral plant leaf images of cucumbers [20]. Some specific features of images are identified using traditional ML classification methods, which involve some issues like difficulty in extracting similar values of image features under different lighting conditions. This also leads to a failure to identify diseased image targets with accuracy. Many of the image sizes, colors, regional distribution, and variations in the crop disease type are inconsistent, which again comes up as another issue in the process of representing them with a specified range. Another difficulty faced is the resemblance of the leaf color background, which causes ambiguity and difficulty in the process of effectively and correctly identifying the diseases in the images. This increases the difficulty of morphological segmentation techniques in the process of extracting the features of the targets with great efficiency. This also interferes with the results of the recognition of the targets.

With the soaring rise of DL techniques, the authors [21] have incorporated the identification of crop pests and the detection of diseased leaf images. These types of advanced techniques are capable of automatically extracting the necessary features of the images considered within a pre-defined range and are non-destructive. All these factors are achieved without the intervention of hyperspectral imaging techniques and with increased speed, better stability, and enhanced efficiency. AI techniques like DL are used to identify potato diseases at a very early stage and accordingly use measures to control them by reducing the intensity of the disease and ensuring enhanced protection of potato tubers at a professional level [22]. Apart from all these, the quantity of pesticides used is also reduced to a considerable extent, which helps in maintaining the food value of the potatoes. The compromised food security caused by the use of pesticides is an inevitable issue in the progress of smart and efficient control of potatoes.

DL shows improved performance due to stronger, more complex, and more accurate neural networks as compared to the primitive methods. These factors have an added advantage in solving the problems of visualization and classification of the images considered for the experiment. The authors [23-25] have given importance to the research using DL, including restricted deep Boltzmann machines (DBM), Boltzmann machines, generative adversarial networks (GAN), deep confidence networks (DCN), CNN, recurrent neural networks (RNN), etc. CNN technology is increasing at a rapid pace, and several high-performing NN models have come up, like YOLO, ResNet, GoogLeNet, etc. These models perform excellently in the fields of speech and facial recognition, vehicle detection, etc.

The authors [26] used transfer learning to allow the creation of network models compatible with datasets based on existing mature CNNs. Multi-label classification and functions of focal loss methods to recognize disease of apple leaves based on DenseNet-121 deep CNN are used by the authors [27]. In the literature [28], compression and splitting methods are proposed for the classification of images as an efficient feature extraction method and for the performance recognition of fine-grained image classification. LeNet CNN was implemented for the recognition of banana leaf disease [29]. The authors [30] used the GoogLeNet CNN to train a model to analyze a plant leaf image dataset of 54,306 images for 26 different disease types in 14 crops with the help of ML. The authors [31] used migration learning to develop an Inception V3 CNN network to determine pests and diseases. A model based on Caf-feNet CNN was developed on the Caffe framework to detect leaf data for 13 crop pests and diseases. AlexNet and GoogLeNet were compared by the authors [32] for recognizing nine pests on a dataset of 14,828 tomato leaves. The network width is increased with the help of the GoogLeNet algorithm, and the depth of the network is decreased using the Inception structure. This also reduces the computation and enhances the performance of recognizing the network.

The architecture of the network is created to narrow down using some parameters, which further alleviates the issue of gradient disappearance caused by backpropagation training of deep networks. Exploring the diagnosis of crop pests with the help of classical models has been proven to give better recognition results in labs, but the DL models used with crop pest images are characterized by deep layers, complicated network architecture, and need a huge number of training parameters. ResNet is used in DL-NN technology as the foundational network where the number of model parameters and computations is too large. Many DL models have heavy computation loads, due to which it becomes difficult to use mobile applications. They also use parameters of more than 10 million. Due to these reasons, it is becoming much more difficult to optimize the CNN models.

3. MATERIALS AND METHODS

The materials required to carry out this research are a dataset of potato plant leaf images, duly split into training and validation datasets in the ratio of 80:20, and classified into three classes.

Data imbalance, a commonly faced challenge of uneven data representation, poses a key challenge to the biases of the learning algorithm. The algorithm will be biased toward the majority of the class of data, even though the majority of the data is not important. This challenge can be overcome using resampling.

Resampling is an effort to level up the unbalanced data. There are two basic ways of resampling:

- Over-sampling → it is the method of adding copies of items in the under-represented class. Figure 2 depicts the process of over-sampling.
- Under-sampling → this method comprises reducing the number of items from the over-represented class. Figure 3 depicts the process of under-sampling.

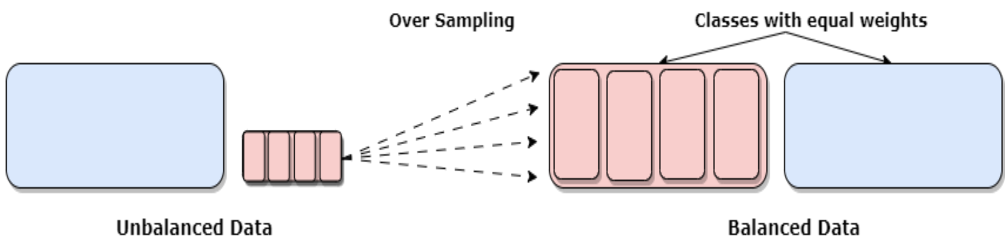


Figure 2. Process of oversampling

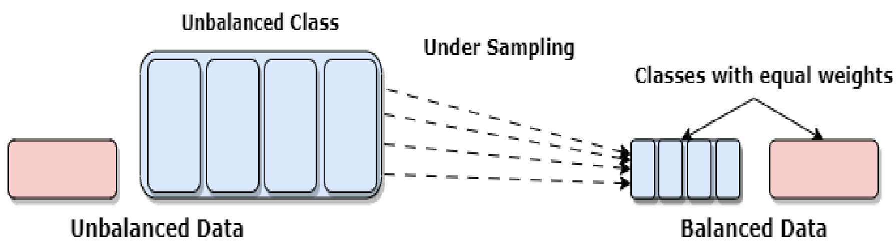


Figure 3. Process of under-sampling

4. METHODOLOGY

The methodology for classifying the potato leaf image dataset using the Inception V3 model comprises various steps. Those steps are listed as follows:

(1) Collection of Image Dataset: This step includes collecting a diverse set of healthy and diseased potato leaf images.

(2) Preprocessing: The images in the dataset are then annotated with specific labels mentioning the category of disease or healthy. The dataset has to be further split into training (80%) and validation sets (20%). The parameters of data preprocessing are:

- Managing missing values.
- Cleaning the data.
- Encoding categorical values.
- Feature creation and selection.
- Data transformation and splitting.
- Data normalization.
- Data handling.

(3) Augmentation of Data: Data augmentation techniques like scaling, rotating, flipping, etc. have to be performed on the training dataset to enhance the diversity of the dataset and prevent overfitting. There are three basic types of data augmentation, namely: image, text, and audio data augmentation. Parameters for image data augmentation can be mentioned as follows:

- The angle of rotation.
- Shifting along horizontal and vertical axes.
- Horizontal or vertical flipping.
- Zoom and sheer ranges.
- Contrast adjustment.

(4) Pretrained Model and Transfer Learning: The Inception V3 pretrained model weights have to be downloaded. This helps speed up the training process by capturing knowledge from a large database. Furthermore, the last classification layer of the Inception V3 model has to be modified to match the classes in the dataset.

(5) Training the Model: The modified Inception V3 model has to be initialized with the weights of the pretrained model. An appropriate loss function has to be defined for the

classification process. A suitable optimizer and a learning rate schedule have to be chosen in the next step. The model has to be trained on the training dataset, and its performance has to be monitored on the validation set.

(6) Evaluating the Model: The trained model has to be tested and evaluated to analyze its performance based on accuracy, recall, precision, and F1-score.

(7) Interpreting Results: Visualization tools are used to gain knowledge about the efficiency of the classification results obtained.

The methodology used to carry out this study is shown in Figure 4.

4.1 Dataset information

The performance of deep learning models heavily depends on an appropriate and valid dataset. A dataset of 2152 potato leaf images, obtained from the Kaggle data source, is used in this research. Out of which, 1937 images are used for training, and 215 files are used for validation. The entire dataset is divided into three classes. An examination of the multilevel classification of early blight, late blight, and healthy leaves is performed, where the three classes are formed, namely: 'Potato Early Blight', 'Potato Late Blight', and 'Potato Healthy'.

The dataset considered for this study consists of three classes, namely the Potato Early Blight class with 1000 files, the Potato Late Blight class with 1000 files, and the Potato Healthy class with 152 files only. Figure 5 shows the data imbalance plot of the three classes of the dataset.

Class weight is a way to add Keras weights to the underrepresented class through a parameter. In the case of underrepresented classes, this method helps in adding weight or importance to the classes with a lesser number of items. In the case of the dataset used in this study, the weight used for class 0, i.e., Potato Healthy, is 4.72; the weight used for class 2, i.e., Potato Late Blight, is 0.72; and the weight used for class 2, i.e., Potato Early Blight, is 0.72 each.

Due to the imbalance in the dataset [33, 34], data augmentation is performed on the dataset before the training process begins. The training dataset is augmented, and a sample of the augmented training data is shown in Figure 6.

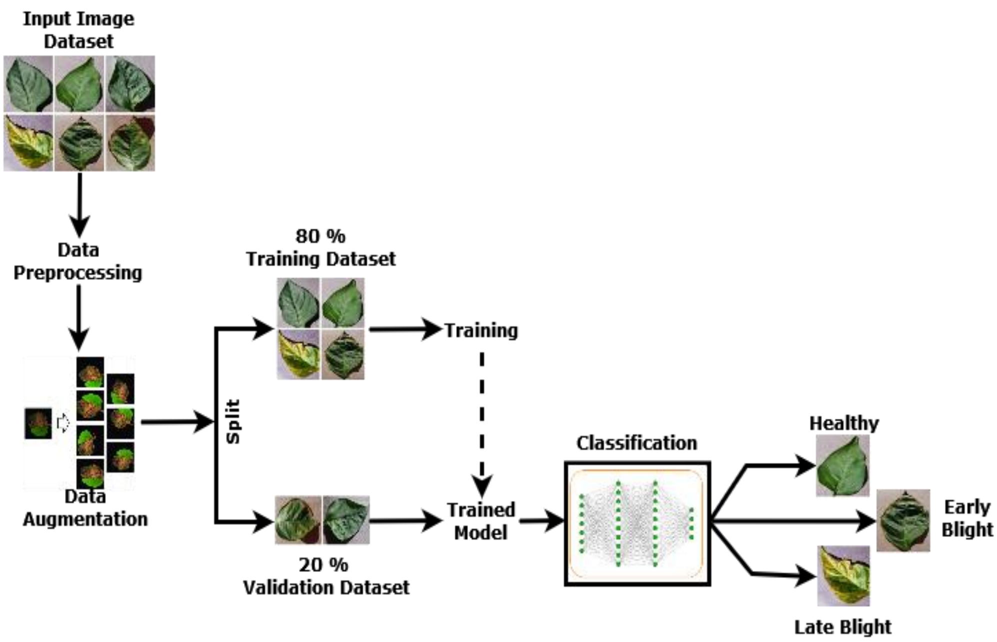


Figure 4. Methodology of potato leaf disease classification using Inception V3 model

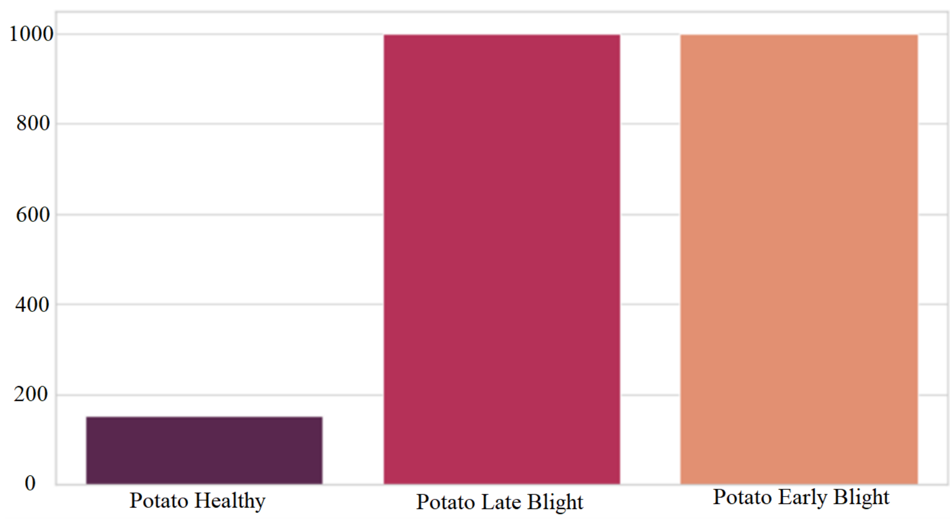


Figure 5. Plot of data imbalance of the three classes of the dataset

Figure 6. A sample of augmented training data

4.2 Modeling of Inception V3

Inception V3 is a CNN model from the Inception family used for image recognition. The main focus of Inception V3 is to use less computational power by altering the primitive inception architectures. Care has to be taken to ensure the computational benefits are continuously attained. Therefore, the use of an Inception network for various use cases becomes an issue due to the irregular efficiency of the network. Several techniques have been suggested to optimize the network to relax the constraint for a simpler adaptation of the Inception V3 model [35-37].

A total of 311 layers are present in this model. The techniques used include dimension reduction, factorized convolutions, parallelized computations, and regularization. A batch size of 128 is considered by the authors for this study with 10 epochs. The Adam optimizer is used to compile the model. Figure 7 demonstrates the workings of the Inception V3 model.

The components of the model can be explained as follows:

(1) Convolution-It is primarily used to extract features like corners, edges, colors, faces, shapes, digits, etc. from the input.

(2) Max pooling layer-It is the type of pooling layer that returns the maximum value from the part of the image that is covered by the kernel. It also acts as a noise suppressant, reducing the dimension.

(3) Concatenation layer-This layer takes an input and concatenates it along a fixed dimension.

(4) Average pooling layer-It is the pooling layer that returns the average value of all the values covered by the kernel. It performs dimensionality reduction only.

(5) Dropout layer-The layer that is responsible for preventing overfitting.

(6) Fully connected layer-This is the layer that comes after convolution layers, multiplies the input with a weighted matrix, and produces an output vector.

(7) Softmax layer-It forms the final layer just before the output layer. It is used to adjust the CNN outputs so that they sum up to 1.

Activation function-The activation function used in CNN is ReLU, which stands for rectified linear unit. The mathematical definition of ReLU can be depicted in Eq. (1).

$$y = \max(0, x) \tag{1}$$

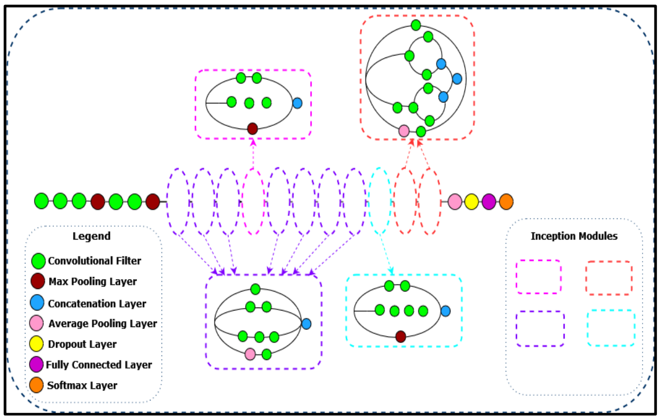


Figure 7. Working on the Inception V3 model

Figure 8 is the simple block diagram of the ReLU activation function.

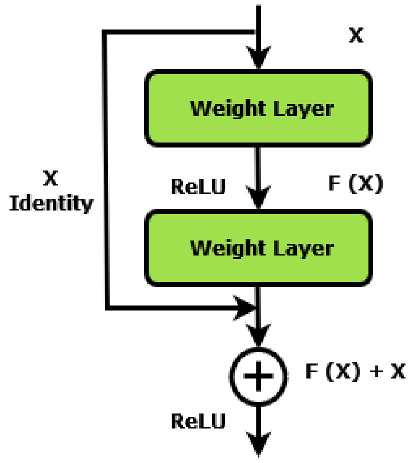


Figure 8. Basic block diagram of ReLU

5. RESULTS AND DISCUSSIONS

The results obtained from implementing the Inception V3 model are discussed in this section.

5.1 Compiling and training Inception V3

Figure 9 is an illustration of the Inception V3 module. Each of the previous layers is passed through various convolution layers as well as one max pooling layer. After processing each of these layers, filter concatenation is performed.

The next step is to compile the model, optimize it using an Adam optimizer, and calculate the loss using a loss function. The metrics refer to the metric that has to be calculated, which is 'accuracy' in this case. After the compilation is done, the model has to be fit to the training data, or, in other words, the model has to be trained. The authors of this study have trained it in batch sizes of 128 with 10 epochs, using 80% of the data as the training dataset and the remaining 20% of the data as the validation dataset. A sequential model is created in TensorFlow Keras that comprises various layers of data augmentation. The layers are defined in Table 2.

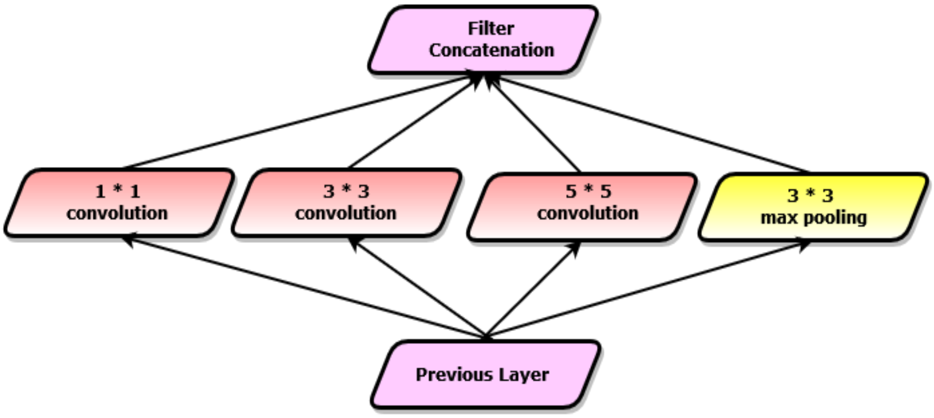


Figure 9. The Inception V3 module

Table 2. Data augmentation layers

Layers	Functions
Random Flip ("horizontal")	It is used to flip the input images horizontally with a 0.5 probability.
Random Rotation (0.2)	It is used to rotate the input images randomly, with a maximum angle of 0.2 radians.
Random Zoom (0.2)	It is used to zoom the images randomly by scaling the height and width to the maximum with a factor of 0.2.
Random Height (0.2)	It is used to apply a random height for the adjustment of input images by scaling the dimension of the height to its maximum with a factor of 0.2.
Random Width (0.2)	It is used to apply a random width for adjustment of input images by scaling the dimension of the width to its maximum with a factor of 0.2.

Table 3. Detailed specification of various training parameters for the CNN model

Layers	Functions
Activation function	Softmax, ReLU
Epoch	10
Batch size	128
Training optimizer	Adam
Loss Function	Cross Entropy

Table 3 comprises details about the various parameters used in the model, like activation functions, epochs, batch size, etc., used in the process of classification.

5.1.1 Accuracy

The evaluation measure used to calculate the classification accuracy is defined in Eq. (2). The number of right predictions divided by the total number of predictions gives the accuracy value.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (2)$$

The model, when trained with 10 epochs with a batch size of 128, gives an accuracy of 98.60% with a validation loss of only 3.63%. Figure 10 shows the accuracies obtained in each epoch.

Figure 11 shows the classification results of the potato leaf dataset. It can be seen that the maximum predictions are correctly made by the Inception V3 model that is used in this study.

```
Epoch 1/10
16/16 - 7s - loss: 0.0169 - accuracy: 0.9923 - val_loss: 0.0410 - val_accuracy: 0.9860
Epoch 2/10
16/16 - 7s - loss: 0.0145 - accuracy: 0.9933 - val_loss: 0.0509 - val_accuracy: 0.9814
Epoch 3/10
16/16 - 7s - loss: 0.0089 - accuracy: 0.9974 - val_loss: 0.0427 - val_accuracy: 0.9860
Epoch 4/10
16/16 - 7s - loss: 0.0089 - accuracy: 0.9979 - val_loss: 0.0416 - val_accuracy: 0.9860
Epoch 5/10
16/16 - 7s - loss: 0.0082 - accuracy: 0.9974 - val_loss: 0.0712 - val_accuracy: 0.9721
Epoch 6/10
16/16 - 7s - loss: 0.0091 - accuracy: 0.9964 - val_loss: 0.0445 - val_accuracy: 0.9860
Epoch 7/10
16/16 - 8s - loss: 0.0059 - accuracy: 0.9990 - val_loss: 0.0534 - val_accuracy: 0.9814
Epoch 8/10
16/16 - 7s - loss: 0.0057 - accuracy: 0.9990 - val_loss: 0.0525 - val_accuracy: 0.9860
Epoch 9/10
16/16 - 7s - loss: 0.0050 - accuracy: 0.9990 - val_loss: 0.0310 - val_accuracy: 0.9907
Epoch 10/10
16/16 - 8s - loss: 0.0037 - accuracy: 0.9995 - val_loss: 0.0363 - val_accuracy: 0.9860
```

Figure 10. Accuracies obtained in each epoch

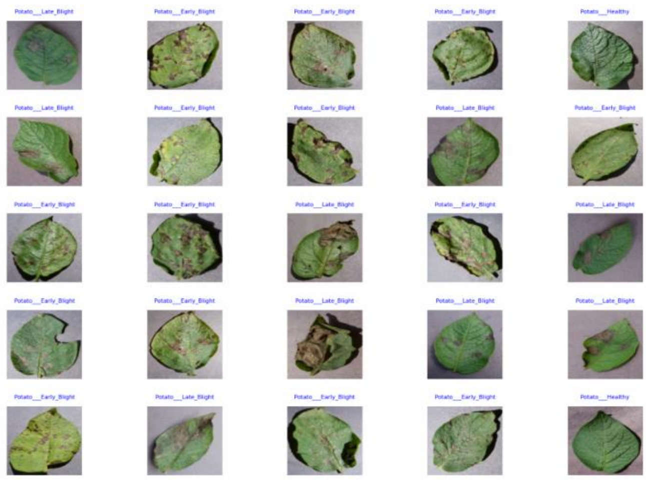
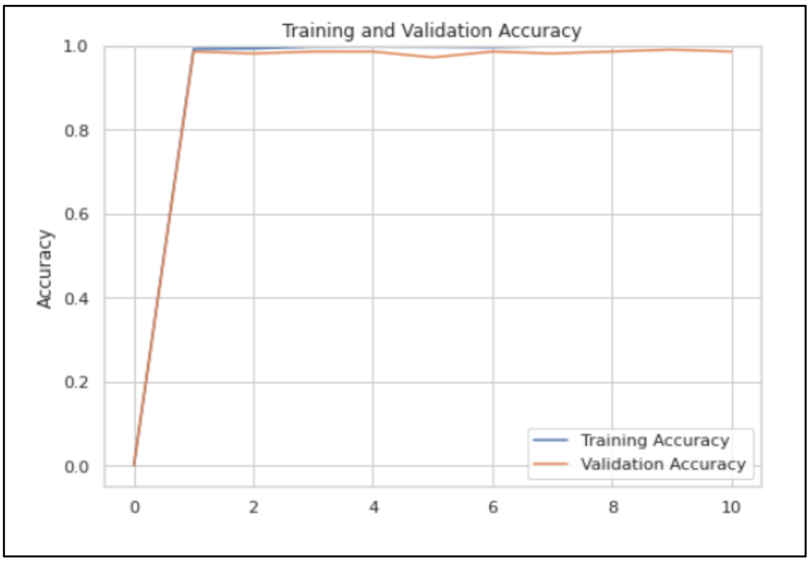


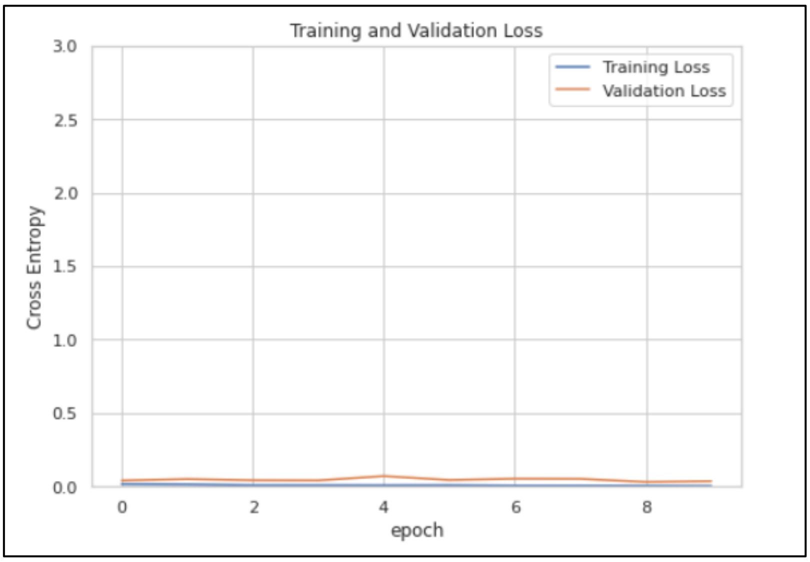
Figure 11. Prediction results of potato leaf dataset

5.2 Plotting accuracy of Inception V3

Evaluate' is a method to evaluate a CNN. The test data are taken as the parameters in this method. Priorly, the 'matplotlib' library and 'show' methods were used to plot the data on the console. Considerably good results were obtained for a specific type of problem using CNN. Figure 12 (a) shows the plot of training and validation accuracy, and Figure 12 (b) shows the plot of training and validation loss concerning different epochs.



(a) Plot of training and validation accuracy



(b) Plot of training and validation loss

Figure 12. Plot of accuracies and losses

5.3 Calculation of other quantitative metrics

Apart from accuracy, there are various other performance metrics like precision, recall, F1-score, mean square error (MSE), root mean square error (RMSE), etc. The authors have calculated the precision, recall, and F1-score in their experiment to better understand the performance of the model.

5.3.1 Precision

Precision is a performance metric used to measure the accuracy of the positive predictions of a model by calculating the correctly predicted positive observations above the total positive observations. The formula to calculate the precision is depicted in Eq. (3).

$$\text{Precision} = \frac{\text{Number of Correctly Predicted Positive Instances}}{\text{Total Number of Positive Predictions}} \tag{3}$$

5.3.2 Recall

Recall is the performance metric used in deep learning classification algorithms, which is used to measure the true positive results out of all the positive cases in the dataset. The Eq. (4) depicts the formula for recall. Recall is alternatively called sensitivity.

$$\text{Recall} = \frac{\text{Number of Correctly Predicted Positive Instances}}{\text{Total Number of Positive Instances in the Dataset}} \tag{4}$$

5.3.3 F1-score

F1-score is the combination of precision and recall, primarily used to strike a balance between these two metrics in cases of uneven class distribution where there is a need to minimize false positive and false negative cases. The formula to calculate F1-score is given in Eq. (5).

$$\text{F1} - \text{score} = 2 * \frac{\text{Precision} - \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

F1-score plays a vital role in assessing the effectiveness of any classification model where there is a lack of clear preference between precision and recall. A tabular representation of all the performance metrics is shown in Table 4.

Table 4. Performance metrics

Accuracy	Precision	Recall	F1-Score
98.60 %	97.03 %	96.88 %	97.56 %

The Inception V3 model is used in this experiment because it has several significant advantages over other CNN models in various computer vision tasks. It used multiple parallel filters, which reduced computational costs considerably while conserving resources [6-9]. It is used as a pre-trained transfer learning model that reduces training time while attaining higher accuracy [9, 15].

Integration of AI techniques in agricultural practices to mitigate crop yield loss due to infestations from early-blight and late-blight diseases holds significant and promising importance in potato cultivation. A rapid detection of early and late blight diseases in potatoes at an early stage can be done with the help of AI-powered systems using image recognition and the analysis of sensor data in smart precision farming setups. Integration of AI also helps in the accurate and precise spraying of pesticides, thus ensuring their optimal use in the farming process. Crop management or recommendation systems can also be developed, which may help in accurate predictive yield analysis and crop planting and irrigation recommendations, ensuring another dimension of efficiency in farming. Such kinds of technologies provide authentic and analytical insights to identify patterns and correlate them.

6. CONCLUSION

Table 5. Comparison between existing works

References	Mosel Used	Accuracy
[15]	Ensemble Classification Technique	89.828%
[16]	Inception V3	98%
[18]	VGG16 and VGG19 CNN	93%
[19]	SVM	95.78%
[20]	Model-based on hyperspectral-terahertz	87.78%
[21]	Fully Convolutional – Switchable Normalization Dual Path Networks based method	97.59%
[24]	ResNeXt101	97.45%
[28]	A new proposed framework called BottleFit	77.1%
[29]	Inception V3	97%
[38]	MobileNetV2	99%
[39]	YOLO 4	98.7%
[40]	MobileNetV2	99%
[41]	MobileNet, VGG16, and Inception	99%
[42]	InceptionV3	97.85 %
[43]	AlexNet	99.33%
Proposed Inception V3 model	**Inception V3**	**98.60%**

Various ensemble and hybrid CNN models are used to classify the leaf diseases of plants efficiently. Table 5 shows a summarized view of the existing works done in this domain and their obtained accuracy. Many of the models provide very high accuracy, but the time required for the entire process of training the model and the process of classification is considerably more than that required in a transfer learning process like the Inception V3 model. It is found that the Inception V3 model used in this experiment outperforms the other models using Inception V3, with the highest accuracy of 98.60% in the minimum time.

The ultimate purpose of this research is to attain faster and more efficient results in the detection of leaf diseases in potato plants. The experimental results revealed that the Inception V3 model used in this experiment outperforms the other CNN models.

Focusing on the severity of the issue of damages caused by plant diseases, this study has come up with an efficient way to diagnose and detect leaf diseases in potatoes. The Inception V3 model plays a vital role in the early detection of plant diseases, which helps in a better and more efficient way to curb the speed of disease spread. Using this model, the limitations of manual monitoring of fields are overcome automatically, and the risk of disease infestation and expanse is mitigated. The authors have focused on the detection of diseases in potato leaves using a considerably large dataset of 2152 image objects. With 80% of the dataset allotted as a training dataset and the remaining 20% of the dataset allotted as the validation dataset, this study shows the feasibility of classification at multiple levels. The accuracy achieved is 98.60%, which showcases the potential of AI-driven solving possibilities for identifying and classifying plant diseases with high accuracy.

Despite having various potential advantages in terms of higher accuracy, lesser complexity, and lesser computational time, the use of Inception V3 can impose various real-life challenges during its implementation. Attaining labeled data and creating a diverse dataset is often a time-consuming and labor-intensive task. Apart from this, there is a need to be continuously updated on the continuously evolving new strains of leaf diseases. Alternatively, various ResNet architectures, MobileNet, DenseNet, etc.-can be used for the classification of leaf diseases and checked for their efficiencies.

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NOMENCLATURE

AI	Artificial Intelligence
EDA	Exploratory Data Analysis (EDA)
CNN	Convolutional Neural Network
DL	Deep Learning
IR	Infra Red
SVM	Support Vector Machine
DBM	Deep Boltzmann Machine
GAN	Generative Adversarial Network
DCN	Deep Confidence Network
RNN	Recurrent Neural Network